Probabilistic models for live victim extrications in Urban Search and Rescue operations after earthquakes

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Abstract – **In Urban Search & Rescue (USAR) operations after large-scale earthquakes, time is of essence for the survival of trapped victims. There are too many parameters that define the conditions, severity and survivability window for each victim entombed under debris. Hence, worksite assessment and triage is primarily an empirical procedure that is based on incomplete and mostly qualitative information. On the other hand, if statistical rescue data from previous USAR missions are available, appropriate probabilistic models can be developed for estimated rescue counts and live victims remaining over time. This study explores the availability of such historic data and, based on these, several probabilistic models are designed. These include Exponential and Weibull for inter-rescue times, non-homogenous Poisson for rescue counts and Generalized Extreme Value (GEV) for the tails of the underlying data distributions. All the models converge to very similar results for survival windows and in accordance to real rescue data. Namely, the 95% and 99% quantiles point to 115-118 hours (4.8-4.9 days) and 177-181 hours (7.4-7.5 days), respectively. A mixed-model approach is proposed for more accurate approximations, selecting GEV for the beginning (up to day 2) and ending phases (days 5-8), Weibull for the middle (days 3-4) and non-homogenous Poisson everywhere else (days 2-3, 4-5), with a relative approximation error no more than 4.5% compared to real rescue data throughout the typical USAR operational period of eight days. Finally, the GEV model is also used for investigating the effect of under-reporting live rescues during the first 24-hour window of USAR operations, providing hints of a factor at the order of 1-in-5 to 1-in-8 or more, especially during the first six hours. These results provide valuable insights for better planning and team deployment in such USAR missions after large-scale earthquakes.**

Keywords – **Search & Rescue, crisis management, USAR, victim triage, risk assessment, survival models, probabilistic models, INSARAG, earthquakes.**

1. Introduction

In Search and Rescue (SAR) missions, the three most critical aspects in operational planning are [1-3]: (a) First Responder (FR) safety, (b) victim survival and (c) situational awareness. Safety always comes first, before speed and efficiency in actual rescue operations, yet the time needed to gain access to the victims is perhaps the most crucial factor for their survival, especially when severe injuries have occurred. Moreover, situational awareness entails keeping track of everything that is happening at the location of the victim and at the same time throughout the disaster area for any major changes in the operational conditions, including weather, aftershocks, etc.

Specifically for **Urban Search & Rescue (USAR)**, where the FR teams are called to work in an environment that is already very challenging in terms of safety and victim detection, time is of essence. Entombed victims under heavy debris face severe dangers from inflicted trauma, external hazards like gas leaks, lack of mobility, as well as lack of food and water that is of vital importance when rescue operations take several days. Even when victims survive the initial disaster event, injuries and overall degradation due to physical and emotional stress act as a countdown for being rescued in time.

The typical profile of USAR operations is after a major disaster event that leads to collapsed structures and entrapment of victims under debris [10-13]. This can be caused by floods (e.g., Nepal, 2026), tsunamis (e.g., Indonesia, 2004), avalanches (e.g., Peru, 1970), landslides (e.g., China, 1920), but earthquakes and structural collapses are the most common case for densely populated urban grids. This covers about 40-50% of USAR deployments with activation of international teams, followed by hurricanes, cyclones, and tropical storms (25-30%), flooding and related incidents (15%-20%), etc. Wildfires used to be associated with a relatively low percentage (5-10%), but recent years have shown that their occurrence rate and severity is climbing up rapidly throughout the world, reaching larger geographical regions and for longer time periods.

The special characteristic of USAR operations after large-scale earthquakes is that the disaster is extensive, access is prohibited and many victims are extremely difficult to reach under debris. At the same time, various types of buildings and construction material allow the formation of *'survivable voids'* [6, 15], e.g., inclined pillars of reinforced concrete that create conditions for entombed but alive victims. Therefore, the countdown for the USAR teams is to detect these victims, breach and clear debris to gain access, and extricate them in time for medical assistance [9, 19]. Not all such victims can be detected, neither accessed and extricated quickly enough. However, the percentage of victims that can be saved is the core of the USAR mission and the reason for international mobilization whenever such disasters occur. The **International Search and Rescue Advisory Group (INSARAG)** is the body that defines the proper guidelines and common procedures for such international missions, so that all USAR teams can cooperate quickly and efficiently under extremely difficult conditions [6].

The challenge of estimating the numbers of rescued and remaining live victims trapped inside debris areas after a large-scale earthquake, flood, tsunami, etc., is a multi-aspect and very complex task even to formulate precisely [5, 13, 26]. The formation of survival voids depends on the magnitude of the earthquake, the type and size of the building, the construction material and overall quality, the type of landscape and geology underneath (propagation effects). On the side of victim survivability, it depends on even more parameters, ranging from age and physical fitness to the time of day that defines activity level in the building (occupants density) [18, 24]. Other external factors also play a major role, like the season and overall weather conditions, inherent hazards in the building, like gas leaks, fires, etc.

Although INSARAG defines a separate operational phase for assessing the 'survivability' and any confirmed or reported victims in each location of collapsed structures [6], the overall prioritization and tasking of the USAR teams remains for the most part an empirical process based almost entirely on human expertise. With so many parameters to consider, and with so many of them being qualitative rather than specific measurements for each collapse, it is nearly impossible to formulate a precise model regarding what is the expected number of live victims remaining trapped underneath the debris of a specific location. Even more, it is practically unknown how many of these victims have severe trauma, if they need immediate medical assistance or if they can survive until the USAR teams manage to penetrate the debris don to their exact spot.

The overall question remains: Is it possible, based on historic data of rescues in previous USAR deployments, to develop probabilistic models that provide even rough but realistic approximations of these numbers, most importantly the rescue count versus live victims remaining?

To answer this question, this study explores the availability of such historic data from major earthquakes internationally over the last several years, taking into account the INSARAG operational protocols and the inherent lack of detailed rescue records, i.e., availability of only aggregated statistical data. Furthermore, in this study the most appropriate probabilistic models are applied to these data, several adjustments and optimizations are investigated and, finally, a compact set of best-fit parameters is calculated for each model, so that they can be used in practice.

The remaining of this study is organized as follows: Section II, presents the problem statement, the main steps, the available historic data that are used here, as well as a very brief summary of the major INSARAG procedures and elements that are of relevance. Next, section III presents the top-level description of the selected probabilistic models used as baseline, along with the way survival probabilities are estimated and how these coincide with the available historic data. In section IV, there are two estimations for the models using slightly different sets of historic data, in order to check the 'ablation' (robustness) of these estimations against specific earthquake events. In addition, specific numbers are calculated for rescue counts based in the most recent historic data, with tables that can be used in practice as-is. The issue of under-reporting of rescues is explored in detail, as well as a proposed mixed-model alternative for better approximations. Section V includes a brief overview of the available literature and related works for survival models, highlighting the importance of having detailed rescue records and a global database from USAR missions. The outcomes from this study are compared to these works, as well as the lessons learned from INSARAG reports after major earthquake events over the years. Finally, sections VI and VII provide an overall assessment of the usefulness of such probabilistic models in practice, under the scope of always having a human expert in the decision-making loop for assessments, triage and prioritization for planning the tasking of USAR teams inside the disaster zone.

II. DEFINITIONS

The following sections describe the problem statement, the available historic data from previous large-scale earthquake events, as well as very brief summary of the most relevant INSARAG procedures and elements.

2.1 Problem Statement

Based on the discussion above, it is clear than not all real-world parameters and external factors can be included in the task of estimating live victim counts, rescued and remaining, via a probabilistic model. On the other hand, historic data from previous events can provide adequate aggregated statistics for correlating these rough estimations with operational time in the disaster areas. Assuming that:

- disaster event is of the same type (earthquake),
- event magnitude is of large scale (at least 7.0R),
- building types, material and quality are comparable,
- USAR team efficiency is more or less the same,

then historic data from USAR operations can be combined and corresponding aggregated probabilistic models can be inferred for the number of live victims extricated against time of operations.

In summary, this is a model estimation and best-fit parameter approximation task that can be defined via three specific steps:

1. Retrieve **aggregated historic data** for live victim extrications against time (hours) after large-scale earthquakes from the last two decades or so (after 2000).
2. Estimate the best-fit parameters for **'rescue count' (RC)** and **'inter-rescue time' (IRT)** models, namely Poisson and Exponential respectively as the baseline, or other compatible models.
3. Calculate the approximate live victim extrications at **specific time thresholds**, e.g., t_{90}, t_{95}, t_{99} with respect to total time and rescues during these USAR operations.

In the first step, the time span for historic data is limited primarily to the two most recent decades to make sure that USAR teams, capacities, equipment and procedures are comparable. The second step refers to the two most common approaches used in such problems, namely the estimation of a **Probability Distribution Function (pdf)** for the event count against time (rate) and a **Cumulative Distribution Function (cdf)** for the summation of event count over time (integration) [23, 27]. In theory, both pdf and cdf are valid approaches for RC and IRT models like Poisson and Exponential, respectively, but in practice either one of pdf or cdf is well-suited for model parameterization based on aggregated statistical data, especially of very low granularity as in this case. This means, for example, that a Poisson model may be better approximated via the cdf rather than the pdf, or that Exponential may be inferred after the Poisson model parameters rather than estimated directly, if the IRT data are very sparse or completely unavailable. Finally, the third step is the reason why we need these estimated models, i.e., to make good approximation against time thresholds of specific interest, usually at 50% and above 90% of the total USAR operations time span. These values enable the creation of easy-to-use reference tables, describing live rescue counts against time and rough estimations of how many more to expect in the remaining operational time.

2.2 Aggregation of historic data

Collection of historic data for victim rescues after large-scale earthquakes is possible, especially when official documentation is published, like the **After Action Reports (AAR)** by INSARAG [6-7] or the corresponding national **Local Emergency Management Authority (LEMA)**. However, in practice it is expected that these data sources are only partially validated, often scattered across multiple documents, sometimes with inconsistencies and almost always affected with severe under-reporting of the 'easy' victim extrications (undocumented) during the first 12 hours or so after the main event.

In order to assemble such a usable data pool for a feasible statistical analysis, multiple research works and official reports from various sources must be combined. The main difficulty is that there is **no standardized global dataset of live victim extrications versus time**; the information must be extracted directly from reports and publications for each earthquake. A list of such large-scale earthquake events that may provide historic data is:

- *1960 Agadir*
- *1968 Dasht-e-Bayaz*
- *1985 Mexico City*
- *1995 Kobe*
- *1997 Venezuela (Cariaco)*
- *1999 İzmit, Turkey*
- *1999 Taiwan (Chi-Chi)*
- 2004 Indonesia (tsunami)
- 2008 Wenchuan, China
- 2010 Haiti
- 2011 Van, Turkey
- 2015 Nepal (Gorkha)
- 2021 Haiti
- **2023 Turkey–Syria**
- **2026 Venezuela**
- ***2026 Colombia***
- ***2026 Indonesia***

In the list above, several mentions need to be made about the exclusion of many of these events from the historic data pooling. First, all major earthquake events prior to 2000 must be excluded as sources of historic data, because they are considered too far away from current INSARAG guidelines and **Standard Operating Procedures (SOP)** [6], especially regarding the equipment and technical tools available today in USAR operations. The 2004 Indonesia tsunami was primarily a large-scale disaster due to the floods rather than the earthquake itself, which was an undersea 'mega-thrust' event. Therefore, type of collapses and damages, as well as the construction material, affected the victim entrapment, injuries and, in the end, the number of live victim rescues.

For the 2008 earthquake in Wenchuan, China, no international INSARAG-certified USAR teams were activated, although some elite teams from a few select countries operated there. Following the earthquake, China fast-tracked and accepted specialized rescue or medical teams from a small group of countries and regions—including Russia, Japan, Singapore, South Korea, Hong Kong, and Taiwan. China's National Team which also operated there had not yet passed certification; the China International Search and Rescue Team (CISAR) was

INSARAG-certified a year later as a USAR heavy team. Therefore, historic data cannot be considered fully compatible with INSARAG SOP, e.g., based on victim extrication forms.

In the earthquakes of 2010 and then 2021 in Haiti, the main exclusion factor is the type of buildings (primarily small huts), construction material (wood and other light-weight), and overall quality of the structures (non-reinforced). Hence, severe collapses were much more probable and with much fewer floors than in an urban grid with large structures primarily built with reinforced concrete or other strong material. Similarly, in the 2011 earthquake in Van, Turkey, urban areas were dominated by mid-rise (4- to 8-story) lightly-reinforced concrete frames with hollow clay brick infill walls. Failures were driven by poor concrete quality, unconfined joints, and soft-story mechanisms. In rural areas almost all constructions were single-story adobe and unreinforced stone/brick masonry bound with mud or weak mortar. In the 2015 earthquake in Gorkha, Nepal, stone masonry with mud mortar (SBMM) and low-strength brick masonry was even more prevalent. Urban and heritage zones were affected by extensive destruction of traditional fired-brick masonry in mud/lime mortar structures combined with heavy timber elements (such as multi-tiered pagodas and historical monuments), alongside poorly engineered frame buildings suffering from soft-story collapses. Overall, these are use cases where poor engineering, weak material and/or unenforced structures make extensive damages and building collapses much more prevalent than in typical urban grids with strong and disciplined construction works, most often reinforced concrete and multi-floor structures.

Finally, the most recent large-scale events that fit the required profile for retrieving historic data on live victim extrications are marked with bold in the list. The 2023 Turkey-Syria case is accompanied with a detailed AAR published by INSARAG [7]; some data are available for the 2026 Venezuela earthquake, but not a full AAR yet (August 2026). For the earthquakes in Colombia and Indonesia, it is too early to have reliable statistics and victim rescue data, so these two events must also be excluded.

In order to make statistics comparable, the victim rescues are normalized against the total number throughout the entire USAR operations time span. Also, it should be noted that verified victim rescues should report elapsed time since the main event (until extrication), rescue type (locals, USAR unit, heavy equipment, etc.) or at least the sum of live victims extricated during each time interval (every 1-24 hours). Since the historic data do not typically contain such details for all victim extrications, aggregated statistical data must be used instead as the baseline or ‘ground truth’.

Taking into account all the previous constraints and exclusions, there are two major earthquake events that fit the profile for getting historic data on live victim extrications:

- **2023 Turkey–Syria:** 6 Feb. 2023; 7.7 and 7.8R magnitude (2 events); main areas affected were Gaziantep, Antakya, Kahramanmaras; estimated total 59,488-62,013 deaths, 140 missing, 121,704 injured (Turkey: at least 53,537 deaths, 140 missing, 107,213; Syria: 5,951-8,476 deaths, 14,500 injured); INSARAG AAR states 300 confirmed live victim extrications [7].
- **2026 Venezuela:** 24 Jun. 2026; 7.2 and 7.5R magnitude (2 events); main areas affected were San Felipe, La Guaira; estimated total at least 6,400 dead, 86,300 injured, 18,100-50,000 still missing (Aug. 2026); no INSARAG AAR available yet.

The fact that for the Venezuela earthquake there are still thousands of people missing in the affected areas makes the estimation of the final victim count inconclusive, even when assuming they most likely refer to fatalities. In addition, not having an official AAR means that live victim count is also inconclusive and unverified. Although numbers are available and of relative credibility when they come from LEMA sources, analytical modeling and fine-tuning of probabilistic models have to be weighted more on the data from the 2023 Turkey-Syria earthquake. The methodology below describes when this is implemented and how this change affects the best-fit model parameters.

2.3 INSARAG doctrine and SOP in USAR

For large-scale disaster events that entail collapsing of structures and victim entrapment, like in earthquakes, floods tsunamis, etc, the most comprehensive and internationally recognized set of SOP is the framework introduced by INSARAG [6], along with the corresponding team certifications regarding the corresponding capacities and response capabilities in USAR missions.

The INSARAG operational ‘doctrine’ is the default international standard for USAR operations, focusing on the fundamental objective of maximizing live victim rescues. More specifically, these guidelines emphasize on:

- Rapid deployment
- Structural triage
- Worksite prioritization (triage)
- Victim location
- Coordinated information management

The operational philosophy is based on maximizing the number of survivors rescued before survivability decreases with time, but the guidelines intentionally *avoid* prescribing mathematical survival models. This is because the **decision-making process for worksite triage is attributed to human expertise**, considering several factors that cannot be quantified adequately. Instead, operational decision-making relies on:

- Assessment, Search and Rescue (ASR) information
- Structural hazard assessment
- Estimated victim numbers
- Expected survivable voids

One of the most fundamental aspects of this SOP framework is the five-phase definition of the USAR operations, based on the operational expected focus and expected outcomes. These are the **Assessment, Search and Rescue (ASR)** levels, described briefly in Table 2.1.

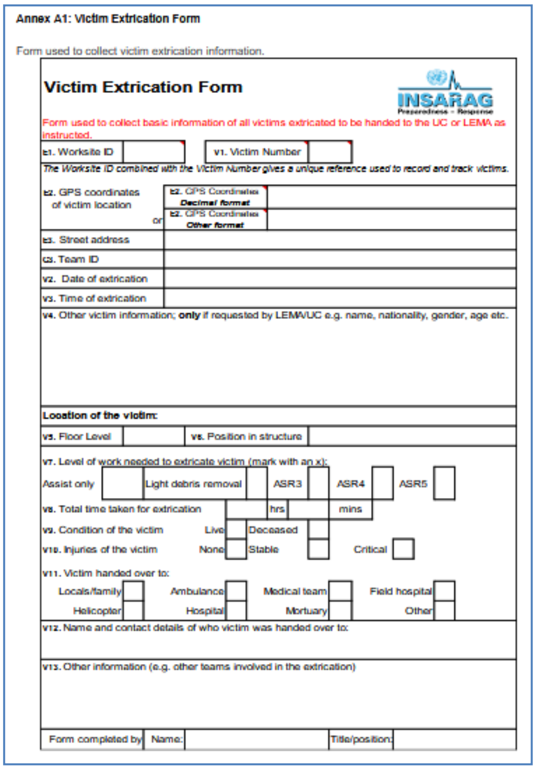
The ASR levels provide a solid and clear outline of how the USAR operations progress over time. There is no strict time window between them and they may be overlapping, depending on the exact timing and extent of the assessment the USAR teams conduct in each worksite. The general rule is that ASR 1 provides the necessary sectorization by LEMA where the USAR teams are directed, and then the teams begin assessing each area in the context of ASR 2, identifying worksites (with confirmed or reported victims) and providing all the preliminary information for a top-level prioritization. Most rescues begin with ASR 3, where victims are either injured and incapacitated on the surface of debris or trapped very close to the surface, thus requiring little time (few hours at most) to be extricated safely. Victims more deeply entombed, requiring many hours of breaching and lifting before the USAR teams gain access to them, are typically in the core of ASR 4 operations. Finally, ASR 5 marks the total recovery of deceased victims inside debris, including any 'late rescues'.

Table 2.1: Assessment, Search and Rescue (ASR) levels, according to the INSARAG guidelines [6].

ASR Levels	Descriptions	Definition and Purpose	Carried out who/when
1	Wide Area Assessment.	Preliminary survey of the affected areas for the purpose of developing the Sectorisation plan, BoO options and overall plan of action.	LEMA/UNDAC/first Responder few USAR Teams in country at the onset.
2	Sector Assessment.	Fast pace methodical assessment to identify viable live rescue sites within assigned sector.	USAR Teams assigned to respective sector.
3	Primary Search and Rescue.	Conduct in early stages – Fairly rapid progress through assigned worksite to maximise lifesaving opportunities.	USAR Team(s) assigned to respective side.
4	Secondary Search and Rescue.	Thorough search through all survivable voids involving full range of USAR capabilities usually at one worksite.	USAR Team(s) assigned to respective side.
5	Full Coverage Search and rescue.	Complete search of entire worksite to locate all life and deceased victims. 2 options for use complete delayering of collapsed structures or room to room clearance of non-collapsed structures.	LEMA, sometimes together with USAR Teams at the of rescue phase.

The coordination of these USAR operations is managed by the **USAR Coordination Cell (UCC)** that is established close to the disaster zone. The main channel of information exchange between UCC and the USAR teams in the 'hotzone' is via set of periodic reports, in hand-written or (more typically) in electronic form, addressing different aspects and context. For example, Figure 2.1 presents a Victim Extrication Form template that is used for hand-written reporting.

Other core reports include the Worksite Triage Form that records the most important information from the ASR 2 assessment of a worksite, subsequently used for worksite prioritization and tasking by the UCC. The prioritization itself takes into account two main factors: (a) if there are confirmed or possible/reported victims and (b) what is the estimated time required to complete the extrication. The first criterion defines whether the worksite is of high, low or no priority (no possibly live victims), while the second whether the rescue operation falls mostly within ASR 3 or ASR 4, which in turn defines the extent of time that USAR teams and assets need to be bound to this worksite. According to the INSARAG SOP, worksite triage is a matter of UCC decision and this is the reason why accurate and timely reporting, especially during ASR 2, is of vital importance.


Annex A1: Victim Extrication Form

Form used to collect victim extrication information.

Victim Extrication Form

INSARAG Preparedness – Response

Form used to collect basic information of all victims extricated to be handed to the UC or LEMA as instructed.

E1. Worksite ID | V1. Victim Number

The Worksite ID combined with the Victim Number gives a unique reference used to record and track victims.

E2. GPS coordinates of victim location | E2. GPS Coordinates ***Decimal format*** | or | E2. GPS Coordinates ***Other format***

E3. Street address

C3. Team ID

V2. Date of extrication

V3. Time of extrication

V4. Other victim information; **only** if requested by LEMA/UC e.g. name, nationality, gender, age etc.

Location of the victim:

V5. Floor Level | V6. Position in structure

V7. Level of work needed to extricate victim (mark with an x):

Assist only | Light debris removal | ASR3 | ASR4 | ASR5

V8. Total time taken for extrication | hrs | mins

V9. Condition of the victim | Live | Deceased

V10. Injuries of the victim | None | Stable | Critical

V11. Victim handed over to:

Locals/family | Ambulance | Medical team | Field hospital

Helicopter | Hospital | Mortuary | Other

V12. Name and contact details of who victim was handed over to:

V13. Other information (e.g. other teams involved in the extrication)

Form completed by | Name: | Title/position:

Figure 2.1: Victim Extrication Form template for hand-written reporting to the UCC [6].

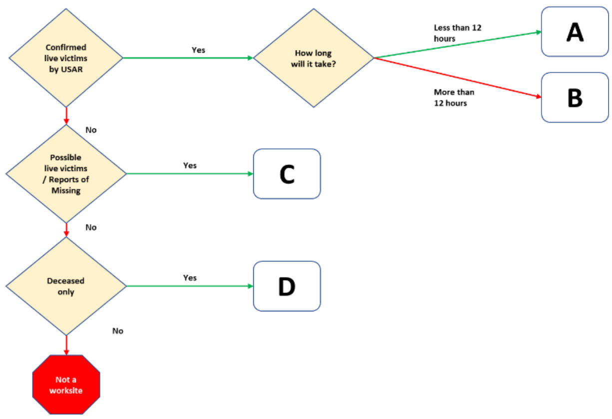


Figure 2.2: Prioritization flowchart followed by USAR teams in the Worksite Triage Form [6].

Figure 2.2 illustrates the simple flowchart followed by

USAR teams conducting ASR 2 worksite assessment. The UCC collects all the Worksite Triage Forms and begins tasking USAR teams to them, starting from ranked list of priority A, then ranked list of priority B, etc.

It should be noted that the complete INSARAG SOP or 'doctrine' consists of several layers of operational and non-operational aspects of USAR missions, ranging from the capacity building for the to-be-certified USAR teams to details about the typical layout of the **Base of Operations (BoO)** in USAR deployments. The **INSARAG Coordination Management System (ICMS)** is one of the key tools for managing the operations and reporting material throughout the USAR mission. Another one is the physical hub of **On-Site Operations Coordination Center (OSOCC)**, or most recently the **'virtual' equivalent (VOSOCC)**. In addition to LEMA, the **Reception and Departure Center (RDC)**, usually set up in the safest airport near the disaster zone, is responsible for registering all the international USAR teams arriving for deployment. Figure 2.3 below presents the overview of interactions between all the main actors according to the INSARAG SOP.

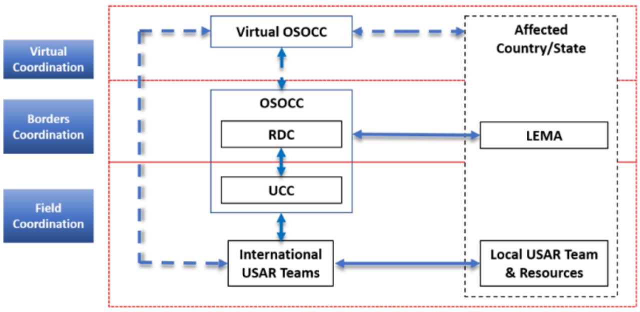


Figure 2.3: Overview of interactions between all the main INSARAG actors during a USAR mission [6].

III. Methods

The following sections describe the selected probabilistic models used as baseline in this study, along with the way survival probabilities are estimated and how these coincide with the historic data.

3.1 Probabilistic rescue models

As previously described, there are two main modeling tasks related to live victim extrication [16-17, 26]: (a) **rescue count over time**, and (b) **inter-rescue time**. Typically, given specific data for one of them, the other can also be inferred, even if these data are only aggregated over coarse time frames, e.g. every 12 or 24 hours of USAR operations.

Since the **rescue count task** is related to occurrence of randomized events over time, the most common and 'compatible' probabilistic model is the **Poisson stochastic process** [22-23, 27]:

$$N(t) \sim \mathrm{Poisson}(\lambda t) \tag{3.1}$$

estimating λ by Maximum Likelihood Estimation (MLE) [27]. The parameter λ is defined as the mean value of event occurrence rate, i.e., in this case the mean number of rescues over time unit.

Similarly, for the intermediate times between randomized events, as it is the case for **inter-rescue times task**, the most common and 'compatible' probabilistic model is the **Exponential distribution** [22-23, 27]:

$$f(t) = \lambda e^{-\lambda t} \tag{3.2}$$

with λ estimated by MLE. The parameter λ has a different meaning here than in Poisson and it is defined as the mean time between subsequent events, i.e., in this case the mean inter-rescue times.

Besides Poisson and Exponential distributions, other alternatives and surrogates can be used instead. More specifically, the **Weibull distribution** [20, 27] is also commonly used for time-to-failure and time between events, especially if 'failure rates' change over time, i.e., the stochastic process is non-homogeneous. This is particularly important in victim rescue rates, because it has been observed that the corresponding 'hazard rates' are non-constant over time and lead to slightly heavier tails due to 'late rescues' (see details later on). In other words, a very small fraction of trapped victims are lucky enough to be on conditions better than the rest and, therefore, have slightly better chances of getting extricated alive even much later than statistically expected. The exact formulation of the Weibull distribution is described later on in section 4.3, together with hints on how it can be used to better approximate extreme-value regions of the available historic data.

Specifically for the extreme regions of the probability distributions in survival models, other specialized models are also used in this study. The **Generalized Extreme Value (GEV)** distribution [21, 27] is typically used when the left and right tails, i.e., ranges before and after the 'core' of the data distribution, are value-constrained (range bounds) and need to be modeled more precisely than via a generic all-data distribution. In practice, GEV targets more on the extremes and outliers than the bulk of the available data. The exact formulation of the GEV distribution is also described later on in section 4.3, together with the best-fit model parameters for the available historic data.

It should be noted that, although rescue-count and inter-rescue-time models are inherently different in meaning, using the corresponding cdf instead of pdf can make them directly comparable. This is because rescue-count cdf measures cumulative rescues up to a specific time, while inter-rescue time cdf measures rescues executed within a maximum waiting time span. In practice, if the inter-rescue time span reference in the cdf is too large, it translates to summation of almost all rescues throughout the total range.

Therefore, when the reference time point is the same for all the models, the corresponding cdf curves can be directly compared after proper adjustments and normalization. This is the way all four probability distributions here (Poisson, Exponential, Weibull, GEV) are considered continuous-valued and can used interchangeably in terms of cdf comparisons, as it will be analyzed later on.

Under normal circumstances when adequate data samples are available, the goodness-of-fit (GoF) [27] can be measured via statistical and information-theoretic metrics, including Kolmogorov–Smirnov, Anderson–Darling, QQ plots, AIC/BIC comparison, etc. However, since data from victim rescues in major earthquakes are extremely limited as explained above, only qualitative comparisons and plot-based assessments can be made in this study.

3.2 Computing survival probabilities

Using the Exponential cdf:

$$F(t) = 1 - e^{-\lambda t} \tag{3.3}$$

and thus:

$$t_p = -\frac{\ln(1-p)}{\lambda} \tag{3.4}$$

the characteristic times at specific thresholds are:

$$t_{95} = \frac{-\ln(0.05)}{\lambda}$$

$$t_{99} = \frac{-\ln(0.01)}{\lambda}$$

or approximately:

$$t_{95} = 2.996/\lambda$$

$$t_{99} = 4.605/\lambda$$

For earthquake comparison, the parameter λ may be estimated separately for each event, together with confidence intervals for assessing the statistical significance of the estimation. However, due to lack of analytical data, in this study the best-fit parameter estimation is pursued primarily upon the aggregated statistical data from all the events where such data exist and are reliable, according to the explanations above. Furthermore, full estimation of confidence intervals is not possible for the same reasons; instead, some ablation study is made using different partitions of the available aggregated data (see sections 4.1 and 4.2), in order to examine the magnitude of variations (if any) in the estimated model parameters like λ here.

Estimates of cdf at t_{50}, t_{90}, t_{95} and t_{99} are typically adequate as a set of reference thresholds. These t_P values roughly translate to a quantitative answer to the question:

- *'At what time reference point* $\mathbf{t_P}$ *the portion of victim rescues concluded thus far is* **P** *(as % of final/total)?'*

As explained above, the reason for creating these best-fit probabilistic models for victim survival and rescues is to be able to estimate these probabilities in arbitrary reference points in time and in much finer granularity, compared to having only few true reference samples for rescue counts every 24 hours or so.

In general, INSARAG reports show that the last live victim rescues occur about 8-10 days after the main events, while the overwhelming majority of them occur within the first 72-96 hours (3-4 days). Taking into account the reports from the two major earthquakes as described in section 2.2, as well as previous empirical experience, the assumptions for the cumulative percentage of all live victim rescues approximately follow the data presented in Table 3.1 below. These values are broadly consistent with the operational timelines described in the AAR and historical USAR experience.

Table 3.1: Approximate percentage of rescues over time.

Time (h)	Approx. rescues (% of final)
24	0.35
48	0.65
72	0.83
96	0.92
120	0.97
192	1.00

Additionally, Figure 3.1 presents the actual rescue count data as reported in the ICMS by the USAR teams operating in the disaster zones after the large-scale earthquake in Turkey-Syria in 2023. It is clear that the underlying process is not a typical homogeneous Poisson process, as it exhibits very evident heavy right tail, i.e., a significant amount of 'late rescues' in the region of 5-8 days after the main event (11-14th Feb).

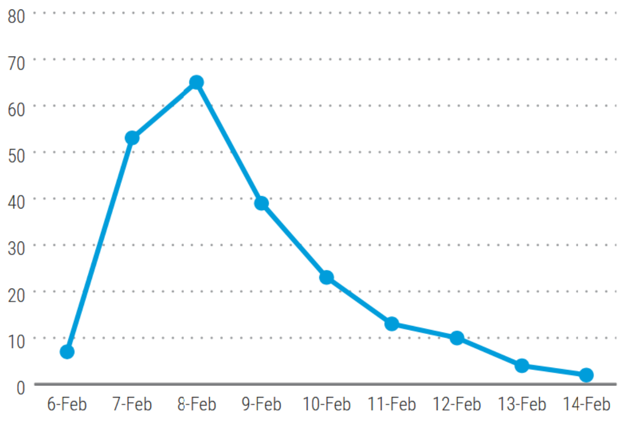


Figure 3.1: Actual rescue count data as reported in the ICMS from the Turkey-Syria 2023 AAR [7].

IV. Results

In this section, two estimations for the models using slightly different sets of historic data are presented, in the sense of checking ablation (robustness). Specific numbers are calculated for rescue counts based in the most recent historic data and tables are presented with the most important numbers. The issue of under-reporting of rescues is also explored in detailed, as well as a proposed mixed-model alternative for better approximations.

4.1 First approximation: 2023 and 1997 data

As explained above, full statistical significance tests for the model parameter estimations are not possible here, due to lack of adequate data. For this reason, pdf and cdf models are estimated using different partitions of the aggregated statistical data and then compared later on with the final models estimated upon the preferred data combination as described, i.e., from Turkey-Syria 2023 and Venezuela 2026 earthquakes.

For the first estimations, only the publicly available after-action information from the **2023 Turkey-Syria earthquake** (AFAD, INSARAG) and the **1997 Cariaco (Venezuela) earthquake** rescue reports are used. The reasons for selecting the 1997 Cariaco earthquake for this ablation study are:

a) It is outside the ‘preferred’ time period defined as valid for USAR rescues data, as explained previously.
b) It is directly comparable in terms of general context (buildings, infrastructure, response readiness) with the 2026 earthquake in that same country.
c) The Turkey-Syria earthquake is still included as part of the aggregated data for reasons of completeness and compatibility with the subsequent (main) model fits.

Based on the methods described above for pdf and cdf, corresponding rough first-order statistical estimations can be developed. It should be noted again that, due to data scarcity, these should be regarded only as practical approximations, rather than a statistically validated models, because the underlying rescue-event data are incomplete.

4.1.1 Inter-rescue times (Exponential model)

Using Eq.(3.3) above for the cdf of the Exponential model, as well as the (observed) reference point at t=72 (hours) from Table 3.1, a direct solution is:

$$F(72) \approx 0.83$$

which therefore gives:

$$\lambda = -\frac{\ln(1-0.83)}{72} \approx 0.0246\ \mathrm{h}^{-1}$$

Thus, the solution for parameter λ is:

$$\lambda \approx 0.025\ \mathrm{h}^{-1}$$

and the corresponding model pdf is obtained as:

$$f(t) = 0.025 e^{-0.025t} \tag{4.1}$$

Based on this model definition, probabilities can be estimated for the same or other reference times, as Table 4.1 shows. Similarly, for predefined characteristic times t_P as described above in Eq.(3.4), the approximate cdf values can be inferred, as presented in Table 4.2. These values align reasonably well with the observation that isolated rescues continued until approximately the 8th day of USAR operations after the 2026 Turkey-Syria earthquake.

Table 4.1: Estimated cdf values for the first approximation (4.1.1).

Hours	CDF
24	0.45
48	0.70
72	0.84
96	0.91
120	0.95
144	0.97
168	0.98
192	0.99

Table 4.2: Estimated cdf values at specific times t_P for the first approximation (4.1.1).

Probability	Time
50%	28 h (1.2 d)
90%	92 h (3.8 d)
95%	120 h (5.0 d)
99%	184 h (7.7 d)

4.1.2 Rescue counts (Poisson model)

Using Eq.(3.1) above for the pdf of the Poisson model and assuming that approximately 8,000 live rescues occurred over roughly 192 hours of active rescue operations (Turkey-Syria, 2023), which is a rough aggregate figure reported during this response, the direct solution for the average rescue rate is:

$$\mu = \frac{8000}{192} \approx 42\ \mathrm{rescues/h}.$$

This is the reference average rescue rate over the entire USAR operations window. In reality, rescue rates were much higher during the first 48 hours (2 days) and then declined rapidly. This is a common observation and suggests a **non-homogeneous Poisson process**, rather than a simple one with non-volatile parameterization.

The corresponding probability mass function is:

$$P(N = n) = \frac{(42t)^n e^{-42t}}{n!} \tag{4.2}$$

Table 4.3 below presents some example values based on this estimation approach. The numbers show that a homogeneous (static) Poisson model is not very realistic in this case.

Table 4.3: Estimated rescue rates at specific time intervals based on Eq.(4.1).

Interval	Expected rescues
1 h	42
6 h	252
12 h	504
24 h	1008

4.1.3 Recommended approximations (both models)

For practical applications in emergency planning and simulation of USAR missions, a practical pair of adjusted models can be the following:

- Exponential inter-rescue distribution:
  - $\lambda \approx 0.025$ h^{-1}
  - Mean inter-arrival time $1/\lambda \approx 40$ h (representing the decay of rescue opportunities rather than the time between individual rescues).
- Poisson rescue-count model:
  - Mean rescue rate $\mu \approx 42$ rescues/h over the full operational period.

If the goal is to model the **declining rescue rate over time**, then a non-homogeneous Poisson process with intensity parameter:

$$\lambda(t) = \lambda_0 e^{-kt} \tag{4.3}$$

is a substantially better representation than a constant-rate Poisson process, as previously defined in Eq.(4.1). Based on this case study of aggregated data from the 2026 Turkey-Syria and 1997 Cariaco AAR, a proper decay constant k for Eq.(4.3) can be approximated:

$$0.020 \leq k \leq 0.030 \ (\mathrm{h}^{-1}) \tag{4.4}$$

Together with Eq.(4.3), this setup provides a reasonable and better modeling for rescue rates. The slowly decaying parameter $\lambda(t)$ instead of a static λ_0, as illustrated in Figure 4.1 below, captures the rapid reduction in successful live extrications after the first three to five days, while allowing rare rescues up to about one week after the main event. The non-homogeneous Poisson process model is generally considered more realistic for operational USAR analyses than a homogeneous Poisson process described earlier.

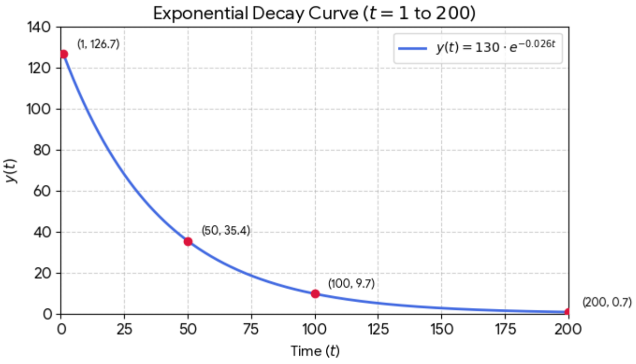


Figure 4.1: Exponentially decaying parameter $\lambda(t)$ as defined by Eq.(4.3) and Eq.(4.4), for λ_0=130 and k=0.026.

4.2 Second approximation: 2023 and 2026 data

According to the list of major earthquakes presented and discussed in section 2.2, the most useful and statistically relevant historic data for victim rescues is from the **Turkey-Syria 2023 and Venezuela 2026 earthquakes**. This is the best tradeoff between selecting recent USAR deployments of international teams according to INSARAG procedures and still not too recent as to lack credible data.

Using the available operational information from these two earthquake events, the recommended model approximations of section 4.1.3 can be revised accordingly. For Turkey-Syria, detailed information from AAR (INSARAG, AFAD [7]) provide rescue timelines over approximately eight days. However, for Venezuela there are no similar final and detailed AAR are not publicly available yet (August 2026); initial reports state that 12 live victims were rescued during the first six days of international operations, but do not yet provide a complete rescue-by-time dataset suitable for statistical fitting. Therefore, the following should be viewed as a **rough calibrated model**, not a proper best-fit optimization in the full MLE sense.

4.2.1 Inter-rescue times (Exponential model – revised)

Using the same approach as described previously in section 4.1.1, a revised parameter approximation can be made using the facts that:

a) Approximately 90–95% of successful rescues by day 5.
b) Essentially all successful rescues by day 8.

Then, the model can be adjusted using:

$$\lambda \approx 0.026 \ \mathrm{h}^{-1}$$

which is only slightly larger than the previous estimate in section 4.1.3 ($\lambda \approx 0.025$ h^{-1}).

The corresponding Exponential model pdf is:

$$f(t) = 0.026 \, e^{-0.026t} \tag{4.5}$$

with a mean characteristic time:

$$E[T] = \frac{1}{\lambda} \approx 38.5 \text{ h} \tag{4.6}$$

Based on this revised model, new reference values can be estimated in Table 4.4, in accordance to Table 4.1:

Table 4.4: Estimated cdf values for the second approximation (4.2.1).

Hours	CDF
24	0.46
48	0.71
72	0.85
96	0.92
120	0.956
144	0.976
168	0.987
192	0.993

These revised values are broadly consistent with the operational observations that successful live extrications become increasingly rare after the first five to seven days. In addition, they are almost identical with the values obtained in the first approximation (section 4.1), i.e., when using the historic data from the 1997 instead of the 2026 in Venezuela. This supports the validity of the models in terms of robustness and low sensitivity to context variations.

Similarly to Table 4.2, for predefined characteristic times t_P and Eq.(3.4) as described above, the approximate cdf values can be inferred, as Table 4.5 shows below.

Table 4.5: Estimated cdf values at specific times t_P for the second approximation (4.2.1).

Probability	Time
95%	115 h (4.8 d)
99%	177 h (7.4 d)

Therefore, according to Table 4.5:

$$t_{95} \approx 115 \text{ h}$$

$$t_{99} \approx 177 \text{ h}$$

4.2.2 Rescue counts (Poisson model – revised)

Using the same approach as in section 4.1.2, revisions can also be made for the Poisson model. However, as previously noted, a homogeneous Poisson process remains only a first-order approximation, because rescue intensity is strongly time-dependent.

Using the combined Turkey-Syria and Venezuela USAR operational timelines, the non-homogeneous Poisson process can be defined as:

$$N(t) \sim \text{Poisson}(\mu t) \tag{4.7}$$

with a reasonable average rate:

$$\mu \approx 35\text{–}40 \text{ rescues h}^{-1}$$

for a large catastrophic urban earthquake over the full rescue period. Here, Eq.(4.7) with parameter μ is identical to Eq.(3.1) with parameter λ.

In practice, the first 24-48 hours have a much higher rate of rescues, followed by exponential decay as described earlier. Therefore, a more realistic intensity function is similar to Eq.(4.3):

$$\mu(t) = \mu_0 e^{-0.026t} \tag{4.8}$$

with $\mu_0 \approx$ 120-150 rescues/h immediately after the main event and then declining with the same characteristic decay constant, inferred from the cumulative rescue data. The exponential decay curve of this formulation, with μ_0=130 and k=0.026, is illustrated above in Figure 4.1.

This non-homogeneous Poisson model better reflects the operational reality reported in both earthquakes than a constant-rate Poisson process. This is because of the heavy right tail of the underlying pdf from the actual ICMS data, as illustrated and explained above in Figure 3.1, It is still very close to the corresponding ‘recommended approximation’ described in section 4.1.3 above, despite the fact that the exponent here is static instead of something similar to Eq.(4.4).

4.3 Third approximation: 2023 and 2026 data for tails

There are several reasons why rescue operations after major earthquakes present special statistical characteristics, particularly during the early and the late stages of USAR operations:

- Due to the scale of the event, LEMA and other regional agencies need some time to organize and coordinate the emergency response.
- Internationally mobilized USAR teams need time to arrive and deploy at the disaster areas in that country.
- There is a large number of ‘quick’ rescues of victims trapped only superficially in partially collapsed structures; these rescues are easy to miss (not reported) during the initial phase of emergency response.
- The large scale of the event and the extensive damages increase the probability of a victims being trapped in ‘unexpectedly advantageous’ conditions. For example, victims only lightly injured but trapped inside a room with plenty of drinking water and some food. These are ideal conditions for the ‘late rescues’.

The first three cases contribute towards **late discovery of victims** and/or **under-reporting of rescues** during the initial phases of the emergency response operations. Thus, they are creating a statistical trend for lower-than-expected rescue counts initially, i.e., a ‘squeezed down’ left tail in the distribution, or a time shift (delay) for a few hours towards the right. Similarly, the last case refers to ‘late rescues’ that enhance the right tail of the rescue count distribution, i.e., more victim rescues than expected at the very late stages of the emergency response. The issue of under-reporting is a very important observation, not only statistical but also empirical in real-world USAR deployments after major earthquake events, and will be discussed in more detail later on (see section 4.5).

Both the left (fade in) and the right (fade out) tails in probability distributions for the rescue count are extremely important in planning and executing emergency response procedures: The left tails, i.e., delays and under-reporting, directly affect triaging of worksites and possible victims therein; the right tails (‘late rescues’) define the optimal allocation of assets in scattered worksites with only few deeper rescues available. Therefore, it is crucial to correctly model these extreme regions of the probability distributions, either in the pdf or the cdf models, depending on the historic data that are available for reference.

Based on the same data from the 2023 Turkey-Syria and 2026 Venezuela earthquakes, a GEV distribution [21, 27] can be used as surrogate of Poisson and/or Exponential distributions that were described in previous sections. In particular, the GEV model can be used as an alternative empirical model, focused primarily on the tails of the underlying probability distribution. However, it is important to distinguish between **good statistical fit** and **physical interpretation**:

- The **Poisson process** remains the natural stochastic model for rescue counts.
- The **Exponential distribution** is the simplest survival model for waiting times, but assumes a constant hazard rate.
- The **GEV distribution** is typically designed for block maxima/minima regions, not waiting times or counting processes. Nevertheless, it can serve as a valid and flexible empirical surrogate for the rescue-time cdf curve if its parameters are fitted to the observed rescue timeline.

With only the approximate cumulative rescue fractions used earlier in Table 3.1, a reasonable Least Squares Error (LSE) fit to the GEV cdf [21, 27]:

$$F(t) = \exp\left[-\left(1+\xi\frac{t-\mu}{\sigma}\right)^{-1/\xi}\right] \tag{4.9}$$

yields approximately the parameter set described in Table 4.6 below:

Table 4.6: GEV model parameters for the available data.

Parameter	Estimate
Location μ	58 h
Scale σ	33 h
Shape ξ	0.12

The positive but small shape parameter indicates a slightly heavier upper tail than the Gumbel case (ξ=0). This creates a loaded right tail (Fréchet type), meaning that extreme values decay slowly as a polynomial rather than exponentially. In general, this leads to a high probability of increased rate of rare events and infinite higher-order moments like variance or kurtosis. This is consistent with the rare ‘late rescues’ observed as isolated cases after large-scale earthquakes.

Using these parameters, the estimated quantiles from the GEV model approximation can be revised according to the values in Table 4.7 below:

Table 4.7: Estimated cdf values at specific times t_P for the GEV model approximation.

CDF	Time (hours)	Time (days)
90%	95 h	4.0 d
95%	116 h	4.8 d
99%	181 h	7.5 d

These values are remarkably close to those obtained with the Exponential model, as shown in Tables 4.2 and 4.5 earlier. This is because both Exponential and GEV are calibrated to the same rescue timeline and here they refer to the same right tail of the cdf curve.

For the **Weibull distribution**, the pdf is defined as [20, 27]:

$$f(x;\lambda,k) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{4.10}$$

where k>0 is the shape (order) parameter and λ>0 is the scale (rate) parameter. The corresponding cdf is defined as:

$$F(x;k,\lambda) = 1 - e^{-(x/\lambda)^k} \tag{4.11}$$

exhibiting a value of approximately: $F(\lambda;k,\lambda)$=0.632, i.e., at the reference point: $x=\lambda$.

A representative Weibull model fit to the same data is:

shape $k \approx 1.35$, scale $\lambda \approx 78$ h

and the best-fit model cdf can provide estimations for reference thresholds t_P, as presented in Table 4.8 below:

Table 4.8: Estimated cdf values at specific times t_p for the Weibull model approximation.

CDF	Time (hours)	Time (days)
95%	118 h	4.9 d
99%	179 h	7.5 d

As explained previously in section 3.1, the Weibull distribution is typically used as a more general model than the Exponential for time-to-failure and time between events. It is well-suited when 'failure rates' change over time, i.e., the underlying stochastic process is non-homogeneous. In practice, this translates to shifts in the tails of the pdf and cdf curves, not approximated correctly by a standard homogenous Exponential distribution.

As explained earlier in section 3.1, although rescue-count and inter-rescue-time models are inherently different in meaning, using the corresponding cdf instead of pdf can make them directly comparable. For the Weibull distribution, it means that cumulative rescue counts can be derived from its best-fit model cdf, just like when Exponential is used instead. The advantage here is that Weibull is more generic, meaning that it can adapt better to non-homogenous stochastic processes and, therefore, is expected to perform better in the tails of the underlying distribution.

4.4 Qualitative comparison and recommended models

Although several adaptations can be made almost to any of the probabilistic models presented earlier, there are some distinct differences between them and justified reasons why use one and not another in each case depending on the task.

Tables 4.9 and 4.10 presented below explain the overall assessment of the main models and how they can be applied on live victim extrications during USAR operations. The first is more explanatory and refers to the cdf approximations for the inter-rescue times, while the second can be more concise and refers to corresponding cdf approximations for the rescue counts. These summarize the observations already made above, based on the model calibrations and the resulting approximations.

Table 4.9: Overall assessment of probabilistic models (mostly cdf-based) for **inter-rescue times**.

Property	Exponential	Weibull	GEV
Timing interpretation	Excellent	Excellent	Poor
Non-constant hazard	No	Yes	No
Fits heavy tail	Limited	Moderate	Excellent
Model parameters	1	2	3
Physical interpretation	Strong	Strong	Weak

Table 4.10: Overall assessment of probabilistic models (mostly cdf-based) for **rescue counts**.

Model	Suitability
Homogeneous Poisson	Fair
Non-homogeneous Poisson	Excellent
GEV	Specialized (tails)

In addition, Figure 4.2 presents typical reference curves for the Exponential, Weibull and GEV distribution models (cdf) when using comparable parameters. It is obvious that a standard Exponential distribution produces a sharp and exponentially decreasing 1st derivative in its cdf curve (quickly smoothing) with heavy weight on the leftmost region, while GEV rises very gradually at that same region, and Weibull residing somewhere in between.

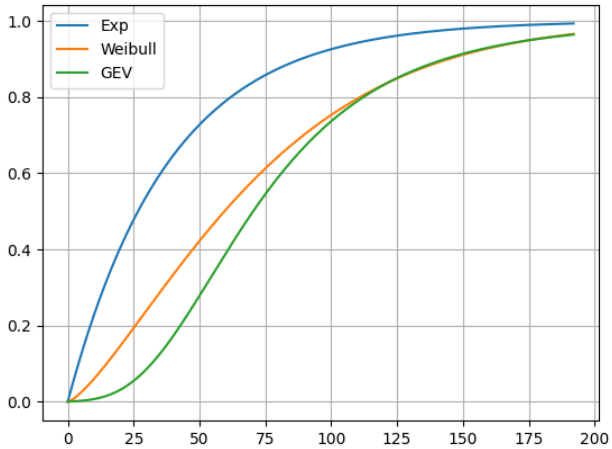


Figure 4.2: Typical reference curves for comparable Exponential, Weibull and GEV distribution models.

In general, the previous results confirm the following intuitive observations:

- **Exponential model:** Predicts the fastest decay in rescue opportunities and provides a simple first-order model.
- **Weibull model:** Delays the initial accumulation of rescues, while producing a more realistic decreasing hazard rate. This can generally be considered as the preferred survival model for USAR operations.
- **GEV model:** Closely follows the Weibull model through most of the operational window, but retains a smaller left tail (more delays) and slightly heavier upper tail allowing for more 'late rescues'.

It should be noted that these assessments do not cover the full aspect of error-related metrics for approximation accuracies, which typically differs depending on the exact range examined, i.e., the time window of USAR operations. This aspect is further discussed later on in section 4.6, along with a combined plot (see Appendix A), suggesting a ‘mode-switching’ approach for better model approximations. Furthermore, the notes ‘poor’ and ‘weak’ in Table 4.9, as well as ‘specialized (tails)’ in Table 4.10 for GEV refer only to the general context of explaining the entire probability distribution range, while in practice GEV is excellent primarily for extremes and outliers in the heavy tails.

Regarding Table 4.10, the most prevalent weakness of the homogeneous Poisson model is that rescue intensity seems to decrease rapidly with time, while in reality this is usually smoother, i.e., creating a heavier tail. Thus, a much better formulation is a non-homogeneous Poisson process with exponentially decaying intensity, as described in sections 4.1.3 and 4.2.2 previously, with:

$\lambda_0 \approx 130$ rescues h^{-1}

$k \approx 0.026\ h^{-1}$

The cumulative expected number of rescues (cdf) is then

$$\Lambda(t) = \frac{\lambda_0}{k}\left(1 - e^{-kt}\right) \tag{4.12}$$

and the probability of observing n rescues by time t (pdf) is:

$$P(N(t) = n) = \frac{\Lambda(t)^n e^{-\Lambda(t)}}{n!} \tag{4.13}$$

Based on the available historic data for the two major earthquakes of interest and the underlying rescue process during the USAR operations conducted therein, some recommendations can be stated in terms of statistical validity regarding the model approximations:

- **Rescue counts:** Use a **non-homogeneous Poisson** process with exponentially decaying intensity. This reflects the operational reality of increased rescue intensity early and progressively decreasing later on.
- **Inter-rescue times:** A **Weibull** distribution is generally preferable to both the Exponential and GEV, as it allows a decreasing hazard rate, while retaining a meaningful interpretation of waiting-time between rescues.
- **GEV:** The best-fitted GEV provides a comparable empirical model to the cumulative rescue curve (cdf) with more emphasis on ‘early’ and ‘late’ extremes and outliers. However, since GEV models primarily the tails rather than event times throughout the range, it is used as an alternative surrogate for these sub-regions of the distribution, rather than the preferred physical model for the entire underlying process.

Table 4.11 below summarizes the best-fit parameters for all the recommended models presented here, adapted to the available historic data from the two major earthquakes of interest. Again, these are the rough estimates of the parameters using only scarce data samples from aggregated ICMS reports as reference points, without hourly updates or victim-specific logs. They are not MLE-optimized estimates from a complete rescue-event database, because there is no such resource available publicly. A statistically rigorous fit would require the rescue timestamps for individual victims from the Turkey-Syria and Venezuela AAR data and would likely produce slightly different parameter values within well-specified confidence intervals. Despite this data scarcity, comparative examination of model adjustments between approximations of alternative versions of these data (see sections 4.1, 4.2, 4.3) confirms remarkably similar cdf results, i.e., expected survival times at specific quantiles.

Table 4.11: Summary of the best-fit parameters for all the recommended probabilistic models.

Model	Parameters
Homogeneous Poisson	$\mu \approx 35$–40 rescues h^{-1}
Non-homogeneous Poisson	$\lambda_0 \approx 130$ rescues h^{-1}, $k \approx 0.026\ h^{-1}$
Exponential	$\lambda \approx 0.026\ h^{-1}$
Weibull	shape $k \approx 1.35$, scale $\lambda \approx 78$ h
GEV	$\mu \approx 58$ h, $\sigma \approx 33$ h, $\xi \approx 0.12$

The comparative values in Table 4.12 below present the estimated fraction of eventual live rescues achieved as a function of elapsed time in USAR operations. These essentially combine the numbers reported previously in Tables 4.5, 4.8 and 4.7, focusing on Exponential (revised), Weibull and GEV models, respectively, i.e., the three directly ‘compatible’ probability distributions. The Poisson model is not included here, because it is a discrete count distribution for rescue counts, rather than a continuous time-density, and not directly comparable with these three (except only via cdf, as explained in section 3.1).

Table 4.12: Summary of the approximate time until two characteristic quantiles of total rescues.

Model	t_{95}	t_{99}
Exponential	≈115 h	≈177 h
Weibull	≈118 h	≈179 h
GEV	≈116 h	≈181 h

The three models in Table 4.12 cluster together very closely to specific reference time points for the typical thresholds of 95% and 99% quantiles of total live rescues, according to the historic data for the two earthquake events of interest. Namely, the first mark is confirmed to be somewhere at **115-118 hours (4.8-4.9 days)**, while the second at **177-181 hours (7.4-7.5 days)** of active USAR operations after the main event. Despite the scarcity of the available data, ablation study and alternative data combinations in three different approximation setups (see sections 4.1, 4.2, 4.3) converge to the same marks with differences of only 3-4 hours, which translates to **deviations of less than 3%** in the corresponding ranges in all cases.

4.5 Assessing the under-reporting of live rescues

One issue of great importance that comes up from empirical work in USAR operations, as well as from the statistical analysis presented in this study, is the increased rate of under-reporting of live rescues, especially during the first hours of the emergency response after the main event.

In Appendix A, Figure A.1 presents the best-fit approximations for all the probabilistic models presented as 'recommended' in this study, more specifically the approximate cdf curves for the models with similar (adjusted per case) parameters of Table 4.11. The selected models are:

- **NHPP(1):** The 'nominal' homogeneous Poisson process with a static parameter λ=0,026 h^{-1}, which is actually the Exponential model suggested in Table 4.11.
- **NHPP(2):** The best-fit non-homogenous Poisson process as described earlier, but with adjusted parameters $\lambda_0 \approx 234$ rescues h^{-1}, $k \approx 0.012\ h^{-1}$ (explained below).
- **Weibull:** The best-fit models with parameters as in Table 4.11.
- **GEV:** The best-fit models with parameters as in Table 4.11.

There is also one additional data series (dashed red line) showing the 'ground truth' of actual rescue counts as reported in the ICMS during the Turkey-Syria USAR operations, which is the test case in these plots. Finally, the grey bars in the supplementary data series (right Y-axis) present the relative approximation error between the best 'spot' model value against the actual ICMS data, meaning that each time the comparison is made with the best approximation by any of the models. The colored vectors on the horizontal axis illustrate which is this 'spot' best model value in each sub-range of the time axis (hours).

The first observation in Figure A.1 is that the approximate cdf curves are very similar (as expected) with the 'nominal' cdf templates shown in Figure 4.2 earlier. In particular, homogenous Poisson / Exponential approximations seem to fail in the early phase (left tail) of the USAR operations, with a high overshoot throughout the actual ICMS data series. Therefore, using a static set of parameters for the exponent λ leads to unrealistic estimations for rescue counts.

On the contrary, all three main models seem to follow the actual ICMS data quite closely, with some differences. The non-homogenous Poisson (NHPP(2)) here is adjusted for a very strict Sum Squared Error (SSE) criterion against the ICMS data as ground truth, thus leading to slightly different parameter values than the ones presented earlier in Table 4.11. Nevertheless, this only affects the 'closeness' of the approximate cdf curve in both tails, as well as the inclination (1st derivative) at the inflection point at roughly the sub-range of 60-100 hours time window. In other words, this adjusted set of parameters closely matches the ICMS data for this specific event and USAR operations, keeping the overall approach identical as previously described.

Finally, the Weibull and GEV models with the exact parameters of Table 4.11 track the ICMS data very closely without the need of any adjustments. Both cdf models seem to be identical after $t \geq 100$ hours, but Weibull remains further away from the ICMS data on the left tail until t=67 hours compared to GEV, which is the overall-best model approximation throughout the range 1-192 hours. In particular, when counting the closest match between ICMS data and any of these three primary models, the result is 38 for NHPP(2), 50 for Weibull and 104 for GEV. The comparison is made for each hour (192 in total) and ICMS data are piecewise-linearly interpolated in between the actual 24-hour data points to generate a full data series.

Taking into account that the homogenous Poisson process (NHPP(1)) clearly overshoots the cdf of the actual ICMS data, this model can be avoided when trying to interpret characteristic properties on the underlying process of live rescues during USAR operations. In contrast, Weibull is the most natural probabilistic model for interpreting inter-rescue times and, thus, expected to 'explain' the underlying stochastic process more accurately for the *entire* time range (not just the tails as with GEV).

The important observation that can be made here about the differences between Weibull and ICMS data on the left tail is related to the under-reporting of live rescues, already explained in sections 2.2 and 4.3 previously. If the Weibull model is expected to closely track the underlying stochastic process of 'arrivals' (rescues), then this difference may be the quantitative *hint* regarding the magnitude and time expansion of under-reporting. In other words, since the Weibull cdf curve closely matches the ICMS data after roughly $t \approx 68$ hours, then its overshoot in the sub-range of roughly $t \leq 68$ hours should be a valid indicator for this under-reporting. This assertion cannot be fully justified due to lack of historic data for both ICMS reports and (most importantly) actual live rescues not reported therein during the first 2-3 days of USAR operations. Nevertheless, since the GEV model can indeed closely match the left tail of the ICMS data and track this 'time lag', the comparative analysis of Weibull-versus-ICMS ('W2ICMS') and Weibull-versus-GEV ('W2G') can be used as a hint.

For this reason, Figure A.2 in Appendix A presents these cdf differences over the first few days of USAR operations. Specifically, the first comparison (W2ICMS) shows a peak under-reporting rate of about 474% at the end of day 1, before dropping sharply and remaining below 50% after day 2. Similarly, the second comparison (W2G) shows a smooth peak of 856% at the mark of $t \approx 6$ hours, then fading out exponentially to less than 50% after $t \geq 51$ hours (2.1 days). There is no clear indicator whether the first or the second estimation for under-reporting is more accurate than the other. However, if the cdf differences are to be interpreted indeed as under-reporting, then it is safe to say that there is such a factor **at the order of 1-in-5 to 1-in-8 or more** within the first day of USAR operations and especially during the first six hours.

The reasons for such high under-reporting rates and the time window that these are happening (left tail) can be summarized as follows:

- Gradual arrival and activation of international USAR teams following the INSARAG protocols, i.e., registering at the RDC, contacting LEMA, getting tasking messages from the UCC, etc.
- Sub-optimal and saturated logistics in the ICMS due to increased workload (UCC, teams) in the first 24 hours, as well as many ‘easy’ victim rescues by locals within the first few hours, i.e., without full reporting to the ICMS.
- Late discovery of victims trapped deeper inside debris, rather than on surface that are usually rescued quickly during ASR 3 operations.

All these factors affect the quality of the ICMS data regarding live victim extrications, which entails detailed reports on a timely manner. Items 1 and 2 are a matter of better organization of the USAR operations overall, including team-level and UCC-level procedures. Importantly, item 3 highlights the **urgent need for developing better technologies, tools and search protocols for locating victims earlier** – preferably within the first 6 to 12 hours, in order to avoid fatalities due to exhaustion and worsening trauma conditions. This comes far and beyond any other priority: Accurate ICMS reporting comes as a supplement to actual victim rescues, not the other way around. This is one of the main reasons why there is still lack of a systematic and validated database of victim rescues during USAR operations over the years.

4.6 A ‘mode switching’ approach for mixed models

As explained above, the colored arrows on the horizontal axis in Figure A.1 (Appendix A), along with the error bars in the supplementary Y-axis series, prove that:

a) The overall approximations fall very closely together (except NHPP(1)) and there is no relative error larger than 4.5% compared to ICMS data.
b) The best-match model selections are clustered together homogenously within only few sub-ranges, meaning that there are specific regions where one model is preferred over the others.

While (a) is crucial for verifying the validity and accuracy of the probabilistic models included in this study, (b) is equally important for demonstrating the strengths and weaknesses of each approximation. In particular, taking into account that Webull and GEV produce essentially the same cdf output after $t \geq 177$ hours (value difference is less than 5.62e-5), the expected outcome is that GEV is definitely the most appropriate model to use in the first 48 hours and then again after the mark of $t \geq 122$ hours, i.e., at the beginning of day 5 of USAR operations. Similarly, Weibull provides the most accurate cdf approximation in the sub-range of $t \geq 68$ and $t \leq 101$ hours, i.e., roughly for the sub-range of days 3- to 4+. And non-homogenous Poisson can be used as best choice everywhere else (two sub-ranges). Table 4.13 summarizes these choices, using the model parameters presented in section 4.5 (adjusted for NHPP(2)).

Table 4.13: Best-choice model approximations of cdf for rescue counts (see section 4.5).

Model	begin	end
GEV	1 h	49 h (2 d)
NHPP(2)	50 h	67 h (2.8 d)
Weibull	68 h	101 h (4.2 d)
NHPP(2)	102 h	121 h (5 d)
GEV or Weibull	122 h	192 h (8 d)

There are several arguments for employing a mixed-model approach for a more realistic cdf approximation of rescue counts and inter-rescue times:

a) There are only few sub-ranges to consider, given the fact that the best-fit model choices cluster together very tightly.
b) The actual ‘mode switches’ between models can be fully automated and transparent to the end-user; for practical purposes, a reference such as Table 4.13 can be used.
c) This mixed-model approach enables phases in the USAR planning that incorporate critical information, such as under-reporting in the first 24-hour time window (especially at $t \approx 6$ hours).

Besides the logical incentive of always employing the best-fit approximation, planning the USAR operations with this information in context essentially provides another meaning to the per-team tasking from the UCC. At the first 24-hour time window it should be expected that only few live victim rescues are reported from worksites, for various reasons described above. Hence, the **USAR teams focus and momentum should not be hindered by low rates of reported rescue counts**, nor be interpreted as a signal that specific worksites present low probabilities for live victims therein.

Similarly, having detailed worksite reports about types of collapse and material, conditions and hazards, etc, over time should provide the necessary historic data for developing such probabilistic models in a much finer granularity and accuracy. For example, the same model-fit approaches may be applied to specific types of collapses, in specific seasonal and landscape conditions, thus providing a **foundational and solid link between worksite triage (ASR 2) and prioritization of victim rescues (ASR 3 and 4)** based on maximum-likelihood live victim extrications.

As explained earlier, this not to be interpreted as automated triage-by-numbers, but rather as a valuable **assistive tool for the decision-makers**, who need to be extremely efficient in tasking USAR teams and resources for maximum survival rates for trapped victims. This approach is still compatible with INSARAG's operational emphasis on time-dependent survivability and worksite prioritization, here with the added advantage of having more accurate estimation about this time-dependent dimension.

V. Related Material

In this section, a brief overview of the available literature and related works for survival models is provided, highlighting the importance of having detailed rescue records and a global database from USAR missions. The outcomes from this study are compared to these works, as well as the lessons learned from INSARAG reports after major earthquake events over the years.

5.1 Validity of the selected probabilistic models

As explained early on, the two most commonly used approaches for modeling 'arrivals' and 'waiting times' in natural stochastic processes are the Poisson and Exponential distributions, respectively. Based on mode specific observations and process properties, these can be further elaborated and specialized according to constraints and known factors. This is why non-homogenous Poisson is recommended over the typical homogenous for the rescue counts, as well as why the more generic Weibull should be considered instead of the Exponential for the inter-rescue times.

The most relevant works supporting these model choices come from the literature in Estimation Theory and survival-analysis models:

1. Rom et al. (2020) [10]: Systematic review of international USAR effectiveness.
2. INSARAG After Action Review (2024) [7]: Operational rescue timelines with aggregated statistics and recommendations for standardized victim-extrication reporting.
3. Abu-Zidan, et al. (2023) [4]: Comprehensive review of rescue and medical USAR operations.
4. Payne & Lutz (1974) [19]: Foundational work on time-dependent prognosis and survival modeling.
5. INSARAG Guidelines (2020) [6]: Current international operational doctrine for USAR. There is a 2026 revision (July) that will come into effect on Jan. 1st, 2027.

These core references provide the strongest foundation for motivating a transition from descriptive rescue statistics towards more formal stochastic models, such as the models presented in this study.

One important conclusion emerges from the existing literature: Although the INSARAG SOP are very precise and clear at the top and medium-level decision-making, modern international USAR practice at the lower levels (hands-on) is still driven primarily by empirical doctrines, operational heuristics, structural triage, and survivability assessment, rather than formal probabilistic rescue-time models. Statistical modeling in these practical aspects of USAR remains an active research gap.

Below there is a brief summary of results and conclusions that are supported by relevant literature review on these subjects, including live victim extrication statistics and survival modeling in USAR operations.

5.1.1 Foundations of survival-versus-time modeling

The earliest quantitative work related to emergency rescue survival is the prognosis-curve framework developed by Payne and Lutz [19]. Rather than modeling earthquake rescues directly, they proposed probabilistic survival curves relating patient survival to elapsed time and medical intervention. Their work introduced the concept that survival probability can be represented as a continuous time-dependent function, which later influenced emergency medical systems and disaster medicine.

Although developed primarily for emergency response in trauma care, this framework established the theoretical basis for using cdf model approximations to estimate survival probability after delayed rescue.

5.1.2 Earthquake victim survivability

A landmark review in *Pre-hospital and Disaster Medicine* by Macintyre, Barbera and Smith [26] remains one of the most comprehensive compilations of documented rescue times from earthquakes. The authors reviewed 34 major earthquakes between 1985–2004, 48 medical publications and hundreds of documented rescues, drawing conclusions about survivability conditions and rates.

Their principal findings include the following:

- Successful rescues continue well beyond the traditional 48-hour window.
- Average latest documented live rescue is ≈ 6.8 days.
- Maximum medically documented rescue is ≈ 209 hours (8.7 days).
- Media reports include isolated rescues after 13–14 days.

Furthermore, the review concludes that existing data are insufficient to construct statistically robust survival models, because rescue timestamps and victim conditions are rarely recorded individually and in systematic ways. This observation is compatible with what is presented in this study and strongly supports the same approach, i.e., approximate statistical models relying on aggregated historical data from USAR operations, rather than individual rescue-event databases which still do not exist.

5.1.3 Statistical models used today

A review of the current literature in this domain suggests several classes of statistical models, most of which are covered here in this study. Table 5.1 below summarizes these approaches, current use in USAR operational planning and suitability in terms of applicability to specific tasks.

Table 5.1: Summary statistical models used today in USAR planning and victim survival models.

Model	**Current use**	**Suitability**
Poisson process	Rarely explicit	Good for rescue counts
Non-homogeneous Poisson	Research	Excellent for declining rescue rates
Exponential survival	Common approximation	Good first-order model
Weibull survival	Increasing research use	Better than exponential because hazard decreases with time
Lognormal	Occasionally used	Good for skewed rescue times
Kaplan–Meier	Disaster medicine	Excellent when individual rescue times are available
Cox proportional hazards	Medical survival analysis	Excellent for patient-level data
Generalized Extreme Value (GEV)	Very uncommon	Useful only as an empirical surrogate for rescue-time distributions

It should be noted that **Kaplan–Meier** [17] and **Cox proportional hazards** [16] models dominate the broader survival-analysis literature, because they naturally handle detailed data of individual victims, something that is rarely available in USAR missions. Therefore, historic data from earthquake rescues are typically incomplete and only available as aggregated statistics, i.e., what is used in this study. Also. the **Lognormal** distribution [27] is typically used as surrogate to Weibull or GEV, when the underlying distribution is skewed and exhibits heavy right tail.

5.2 Lessons from international USAR missions

This section includes four important elements related to INSARAG SOP and lessons learned from previous USAR missions over the years. These are all related to USAR operations effectiveness, worksite prioritization and, most importantly, how they affect the rescue probabilities.

5.2.1 Lessons from recent after-action reviews

The Turkey-Syria 2023 INSARAG AAR [7] identified an important weakness in current international practice: There is still no standardized global database of rescue-event timing. This is despite the fact that Victim Extrication Forms are used extensively used during USAR operations, because they are primarily targeted at aggregated reporting to the UCC, rather a systematic logging of conditions, assessment and treatment in each case individually.

Recommendations in this AAR include simplifying the Victim Extrication Form, improving digital reporting, collecting rescue timestamps, linking victim treatment and extrication records. These recommendations demonstrate that the international USAR community recognizes the need for improved statistical data collection, which is a prerequisite for rigorous stochastic modeling of victim survival and rescues.

5.2.2 Evaluation of international USAR effectiveness

A major recent review published in *BMJ Global Health* [10] examined whether international USAR teams measurably increase the number of live rescues. One of its most important conclusions is that detailed rescue-event information is rarely available and most published analyses report only total numbers rescued, i.e., aggregated data over 12- or 24-hour windows. Operational details such as rescue time, victim condition, equipment used, and extrication duration are generally not recorded or missing from the official reports.

The authors specifically recommend a more systematic recording of victim extrication data to support future evidence-based modeling. This recommendation directly supports the development of probabilistic rescue-time models, such as those discussed in this study.

5.2.3 Structural triage and worksite prioritization

Recent technical reports from INSARAG and elsewhere [7-8, 14, 25] converge on the empirical conclusion that successful rescues depend primarily on prioritizing viable worksites. According to the guidelines (primarily during ASR 2), current prioritization considers:

- probability of survivable voids,
- likelihood of live victims,
- structural stability,
- estimated rescue duration,
- available resources.

This is effectively a **Bayesian decision problem** [27], although it is not expressed mathematically as such in the current doctrine. This is because it is extremely difficult to assess and quantify all these factors in probabilistic terms, while it is even more challenging to formulate the exact *conditional* probabilities for each combination of factors, as a complete Bayesian model requires. For example, individual probability estimations are required for ‘probability of survivable voids’ and ‘likelihood of live victims’ separately, and then another probability estimation for these two combined. In practice, this means a probability $P(B)$ of having survival voids of specific type regardless victims, a probability of live victims $P(A)$ regardless of survival voids, and then the conditional probability $P(A|B)$ of live victims *given* the existence of survivable voids, according to the Bayesian rule [23, 27]:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{5.1}$$

The individual factors cannot be considered statistically independent by default, i.e., the existence of survivable voids is known to be strongly correlated with finding live victims. Thus, this Bayesian formulation expands in a combinatorial way in relation to the number of individual factors under consideration and each case must have adequate statistical data to support valid probability calculations as a baseline for further estimations on the conditionals. Therefore, direct application of such Bayesian modeling is rarely used in practice.

5.2.4 Damage assessment and rescue probability

Large-scale earthquakes incorporating various types of damage mechanisms, building and material types, etc, can provide valuable insights about the way damage assessment is conducted in real-world USAR operations. As a result, rescue success depends jointly upon:

- Structural collapse mechanism.
- Remote damage assessment.
- Victim location probability.
- Operational prioritization.

Although no well-defined probability distributions are provided in the literature as approximate models, it is understood that rescue probability should be continuously updated as new information becomes available. In other words, the selected models that are presented in this study can be fine-tuned upon any specific operational data that may become available, even during the USAR operations.

5.3 Research gap and contribution of this study

Across all of these studies, a set of specific and consistent limitations is evident:

1. No international database contains individual live-victim extrication timestamps.
2. Few publications report rescue times beyond broad intervals, typically of 12- or 24-hour windows.
3. Stochastic parameter estimation is therefore uncommon.
4. Most analyses remain *descriptive* rather than *predictive*.

These limitations explain why operational doctrines in USAR deployments still rely primarily on experience-based prioritization and ad-hoc assessment, rather than formal probabilistic forecasting of viable rescue windows.

Depending on the availability of adequate historic data collected from USAR missions, more detailed and accurate probabilistic models can be developed over time. For each of the factors reported previously for damage assessment and structural triage versus victim survivability (sections 5.2.3, 5.2.4), worksite prioritization and viable rescue windows may be assisted **for each specific worksite**, as explained in section 4.6 earlier. That is, instead of an empirical assessment during ASR 2, each location would be tagged with a specific probability of trapped victims and estimated survivability time windows – a huge leap towards optimizing the assignment of USAR teams and assets inside the disaster area.

In terms of a Bayesian probability perspective (see section 5.2.3), worksite-specific probabilistic models could provide some finer detail in terms of 'local' preconditions and time windows for live victim rescues. For example, in a worksite with a specific type of collapse and construction material, such a model could estimate the cdf margins for t_{95} and t_{99} rescue windows, *not* closing the worksite sooner even when there are data of verified or possible victims therein. In essence, it is context- and time-refinement of the existing worksite prioritization methodology already used in INSARAG SOP [6] and presented earlier in Figure 2.2.

VI. Discussion

Taking into account the analysis presented in section 4.4, as well as the Tables 4.5, 4.8 and 4.12, it is evident that there is a very tight clustering of estimated time marks for 95% and 99% quantiles of cumulative rescue counts. There are some obvious operational and other reasons for this observation. More specifically, these converging approximations produced by several different probabilistic models may be explained partially by the implementation of the same SOP by all the deployed USAR teams, every time employing the same procedures, triaging, ASR level progression, etc. However, there is no hard 'switch' that forces the USAR to suddenly change the SOP phase everywhere in the disaster zone with only such a narrow time difference. In other words, there is no 'external' operational factor enforcing an area-wide phase change in USAR operations, including the ASR levels which may be overlapping or delayed depending on the situation at each worksite. Therefore, these time marks seem to be more associated to **natural physical limits of survivability** for the very large pool of trapped victims after such major earthquakes. This is why both the model approximations (see Tables 4.1, 4.4) and the empirical conclusions from actual AAR show that **45-46% and 70-71% of total rescues are performed within the first 24 and 48 hours, respectively** – roughly two days is the typical margin of a human surviving without water, even when no major trauma has occurred during the entrapment inside collapsed structures.

Similarly, the cases of 'late rescues' that are mapped statistically to heavy tails in the probability distributions are almost always linked to trapped victims sustaining only light injuries and being in very advantageous environmental conditions. Most importantly, a critical factor for a successful 'late rescue' seems to be having food and water supplies at arm's reach, either due to the type of collapse and specific use of the room with the survivable void, or when USAR teams manage to reach the victim early on and provide provisions, while the rescue operations are in progress for many hours or even days.

These 'statistical' observations, already known empirically and in addition confirmed by the model approximations, are key insights for planning and executing performant USAR operations. Worksite triage depends heavily on survivability assessment of confirmed and reported victims; hence, having more precise time marks of the rescue timeline is of utmost importance in real-world disasters. This does not mean abandoning confirmed victims for which their reaching time seems to be outside this survivability profile, but rather managing the USAR teams better in terms of prioritizing worksites when only unconfirmed victims have been reported. Shorter rescue times increase the overall throughput in number of rescued victims, while also increase the survivability of each individual victim, especially when more severe trauma mechanisms are involved, e.g., head injury, crushed limb, hemorrhage, insufficient ventilation, etc.

Table 6.1: Qualitative assessment of various probabilistic models that can be used in statistical analysis of historical rescue data.

Quantity	Preferred model	Justification
Number of rescues over time	Non-homogeneous Poisson process	*Models the rapid decline in rescue activity after the first 24–72 hours while remaining interpretable operationally.*
Time to live extrication	Weibull survival model	*Captures a decreasing hazard rate and is widely accepted in survival analysis.*
Survivor probability	Kaplan–Meier (when individual rescue times are available) [17]	*Non-parametric benchmark requiring no assumed distribution.*
Covariate effects (building type, collapse mechanism, team arrival time)	Cox proportional hazards [16]	*Standard framework for incorporating explanatory variables.*
Extreme late rescues	GEV (supplementary)	*Useful for describing the tail of rescue-time distributions, but not as the primary operational model because GEV is intended for extremes rather than event-time processes.*

Table 6.1 summarizes the probabilistic models that may be used in similar studies and statistical data analyses, describing the qualitative and practical aspects of each choice, as well as the justification of use. It is evident that model granularity depends almost entirely on the availability of appropriate data to support it.

As described previously, the available historic data of live rescues in USAR operations after major earthquake events of the last two decades or so lead to a combination of a **non-homogeneous Poisson process** for rescue counts and a **Weibull model** for live-extrication times, or combinations with GEV when cdf is the target. These choices are statistically well-founded, as they align with the disaster response literature, and remain compatible with INSARAG's operational emphasis on time-dependent survivability and worksite prioritization.

VII. Conclusions

Worksite and victim triage remain a human-based decision-making process in modern USAR operations. Nevertheless, having simple yet accurate probabilistic models for rescue counts and live victims remaining may be of vital importance in assisting these decisions with relevant and practical information.

This study explores the availability of historic data of rescues from previous large-scale earthquakes, applying appropriate probabilistic models and developing best-fit approximations for the entire operational window. In addition, it explores the actual magnitude of under-reporting in live rescues during the first 24 hours and proposes a mixed-model approach that exhibits relative error no more than 4.5% compared to real ICMS data. This proves the validity of these probabilistic models, as well as their potential in applying them to a much more granular spatial level, up to per-worksite if such historic data are made available in the future via a global USAR database.

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APPENDIX I

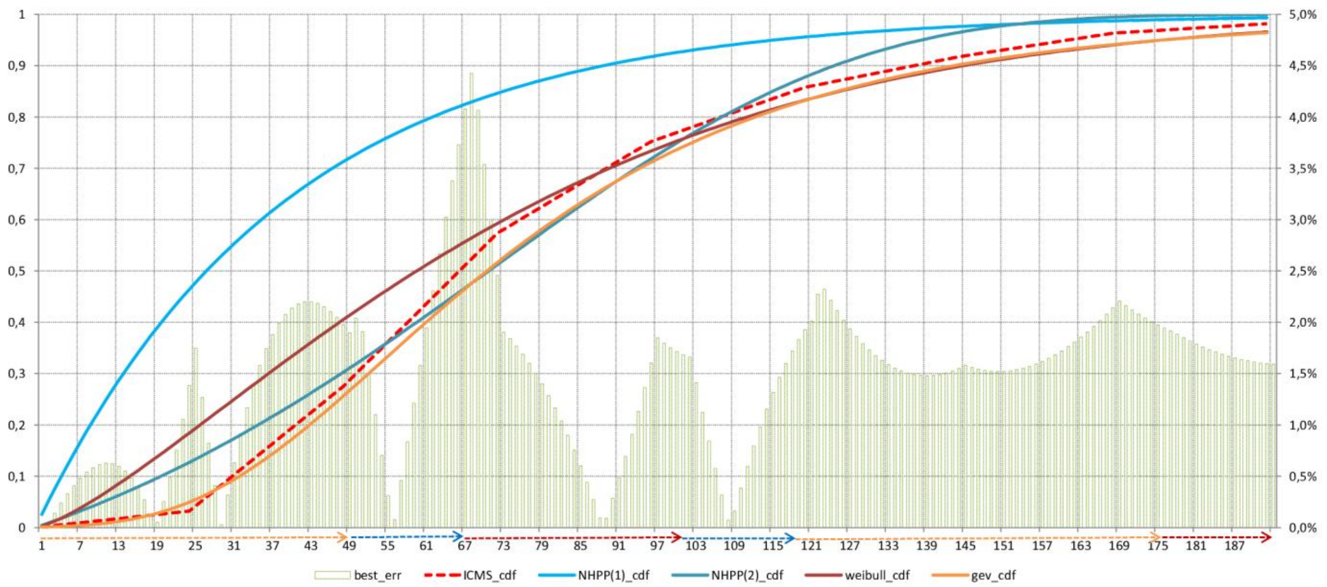

Figure A.1: Best-fit approximations for all the probabilistic models presented as 'recommended' in this study. *NHPP(1)*: 'nominal' Poisson / Exponential (homogenous) CDF; *NHPP(2)*: non-homogenous Poisson CDF; *Weibull* CDF; *GEV* CDF; *ICMS*: real aggregated data with piecewise-linear interpolations; *best_err*: against the best sub-range model approximation (See section 4.5 for details).

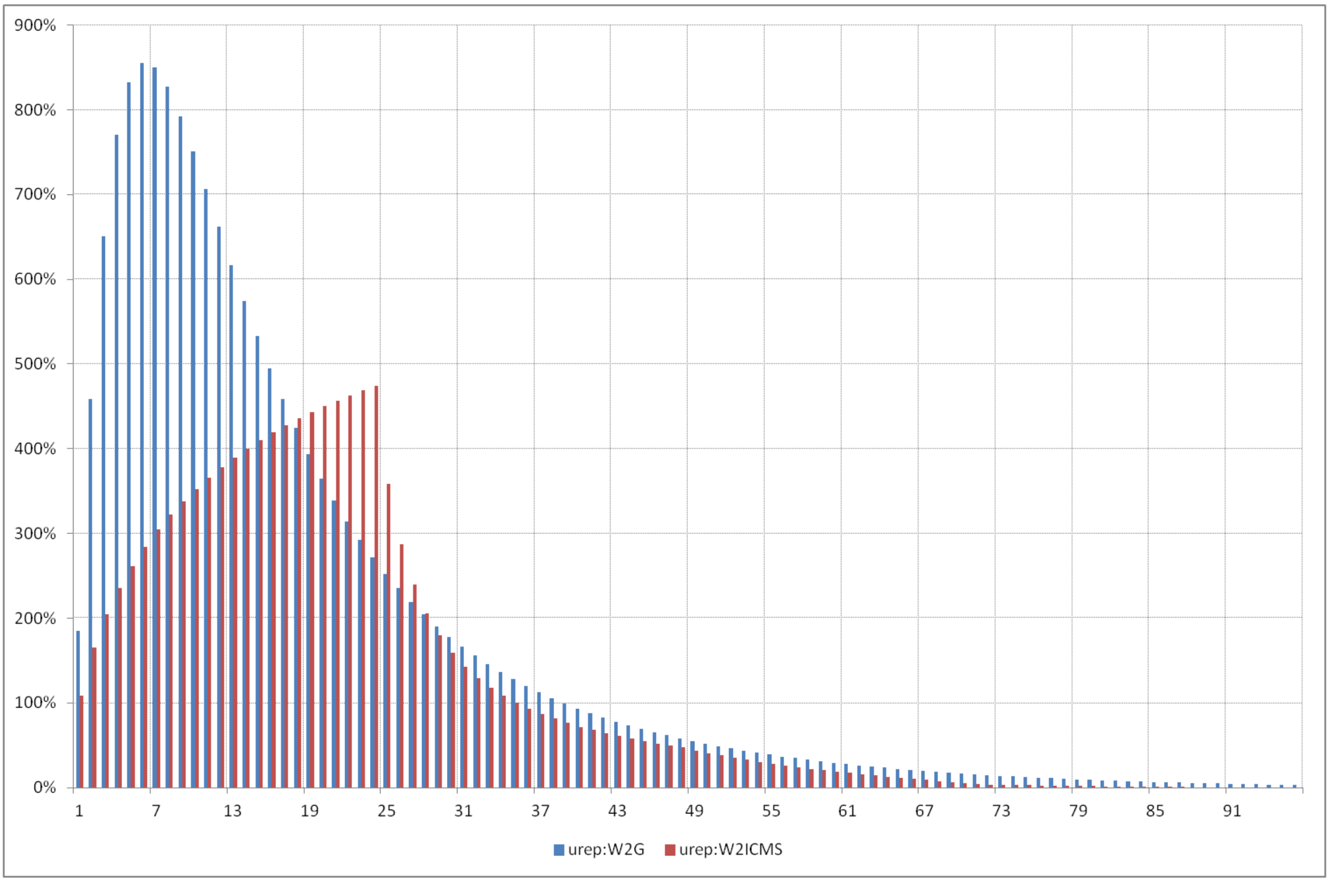

Figure A.2: CDF differences over the first few days of USAR operations. *W2ICMS*: Weibull-versus-ICMS; *W2G*: Weibull-versus-GEV; *ICMS*: real aggregated data with piecewise-linear interpolations (See section 4.5 for details).